DEFECT CLASSIFICATION IN ACTIVE THERMAL TESTING WITH THE USE OF NEURAL NETWORKS

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Thermal testing is widely used in various industries due to a number of advantages. The nature of differential temperature signal obtained from the results of active thermal non-destructive testing depends on many factors, including: measurement time, heating parameters, intensity of heat exchange of object of testing (OT) with the environment, OT thickness, thermophysical properties of OT, geometric dimensions, depth and other characteristics of defects, etc. All these factors are complicated in one another [1]. In practice, it is virtually impossible to establish clear class boundaries for the effective classification of defects by traditional mathematical or statistical methods.

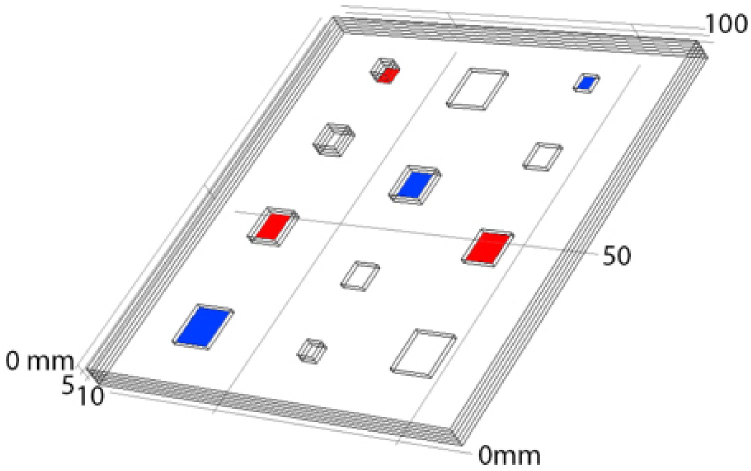
Significant trend in the development of modern data processing systems is the use of artificial intelligence, in particular, neural networks (NN). Thanks to special training algorithms, neural networks are able to automatically detect complex hidden patterns in the relationships between input data. NN are capable for solving multi-parameter tasks and can effectively work with complex nonlinear dependencies, so they can be used as classifiers of images and means of constructing regression models [2].

The authors of [3] investigated the possibilities of using neural networks for testing products made of multilayered materials. Resulting binary map of defects was not inferior in quality to similar maps obtained by traditional methods. The benefits of using neural networks in this work are demonstrated at a qualitative level. Possibility of using neural network classifiers is noted and proved. In [4], a neural network is used to construct defect maps and classify defects by depth. Obtained results show that NN have greater efficiency compared to other methods. At the same time, there are no researches on effectiveness of NN in defining the type of defects, impact of network architecture, or the quality of training dataset on output.

At the present stage of development, there are many different types of neural networks used in a wide range of tasks. Choosing the type of NN is an important task, as each model of network is optimized for specific profile tasks. In thermal testing, the most investigated are classifiers based on multilayer backpropagation networks. Such models are the most versatile and used in both classification and regression tasks. It is known that this type of NN has the best approximating properties, which is why their layers are part of topologies of many other networks [5]. In thermal testing, feedforward networks can be used for both thermogram processing and defect classification and defectometry tasks.

During the training of neural network classifier, it is assumed that for each input vector there is a paired target vector that specifies the required output (response) of NN. Together, these vectors are called training pairs. The training dataset consists of a large number of such training pairs. In tasks of defect classification in thermal testing, temperature profiles of the OT sections are input vectors $X_{in}[n]$. Length n of input vector is the number of thermograms in sequence. The target vectors are $Y_{target}[m]$, which contain a binary code corresponding to the class number. Length m of target vector depends on the number of classes, which in turn is determined by number of possible types of defects.

Let's look at neural network classifier work on a computer simulation. A square-shaped CFRP plate with 100 mm side and 10 mm thickness is selected as object of testing. The plate contains artificial internal defects in the form of square air cavities and aluminum or paper inclusions of various sizes, depths and thicknesses. Schema of OT with internal hidden defects is shown at fig. 1a. At this figure, air cavities are shown by white color, blue and red colors correspond to aluminum and paper inclusions respectively. The OT computer model is implemented in COMSOL Multiphysics software. Testing was carried out in a two-way scheme. A heat source with a power density of 10 kW / m^2 is attached to the upper face of plate. Duration of the heating pulse is set to 1 s, simulation of OT cooling process took place over 14 s. The total duration of thermograms recording is 15 s. Sequence of 50 thermograms, that reflect the entire process of heating / cooling of OT, was obtained on simulation results. Thermogram at the optimal testing time is shown in fig. 1b. Obtained data were exported to MATLAB for further processing.



a

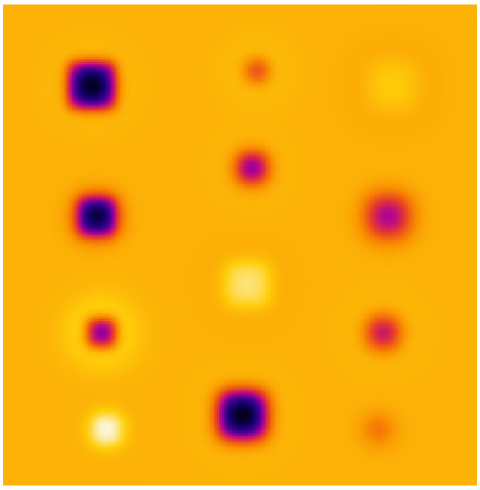

b

Fig. 1. Computer simulation: a – test specimen schema, b – optimal thermogram

Three additional computer models of similar sample plates were created for NN training. These models contained artificial defects of known sizes with different parameters. Each sample contained defects of one particular type: air cavities, aluminum inclusions, paper inclusions. Heating and cooling, as well as thermograms recording were done under similar to the test specimen conditions. Temperature profiles of the corresponding defects were used to form a set of training data.

Consider the work of a neural network to process a simulated thermograms sequence. To do this, a multilayer backpropagation neural network was built in MATLAB using an integrated Neural Network Toolbox module. The number of neurons in input layer corresponds to the number of thermograms in sequence and is $i = 50$. The number of neurons in hidden layer $j = 10$, the number of neurons in output layer $o = 4$. Hyperbolic tangent was used as activation function for neurons. Such a network structure has been empirically chosen since there is currently no single approach to selection of NN parameters for use in active thermal testing [6].

The number of output layer neuron, which have higher numerical meaning, corresponds to the number of defect class identified. The following class definitions were used:

- Class 1: defect-free area;
- Class 2: air cavity defect;
- Class 3: aluminum inclusion defect;
- Class 4: paper inclusion defect.

Obtained map of defects is shown in fig. 2. We can see insignificant shape changes for some defects. According to the results of work, neural network provided an error-free recognition of defects type. The value of relative error of defect area determination is 13.13%. Value of Tanimoto criterion, which is used in pattern recognition theory for determining recognition quality, are obtained [7]. Value of Tanimoto criterion at 88% indicates high reliability of classification results.

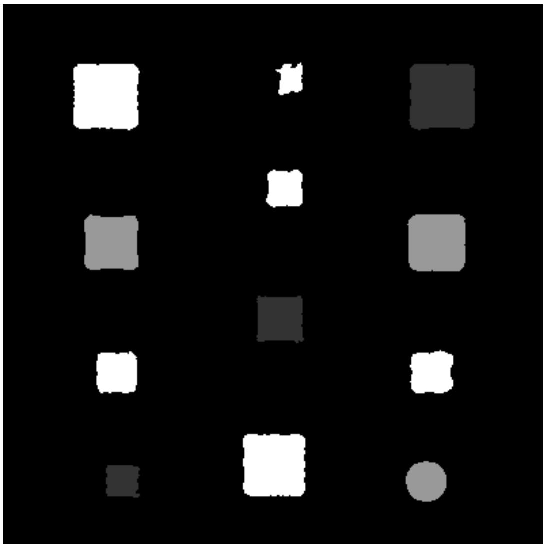


Fig. 2. Map of defects

As conclusion, the use of NN allows to automatically determine the technical condition of object, to build a map of defects and classify them by type or other parameters. NN generalizing capabilities make them an effective means of processing active thermal non-destructive testing data. Due to its high adaptability and versatility, it is promising to use NN in complex systems of thermal field analysis. Disadvantage of this approach is the need for a voluminous training database and the lack of a single approach to determining optimal architecture and network settings. The main direction for further research is optimization of the architecture and parameters of NN to determine the depth and thickness of defects.

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